Available online at www.sciencedirect.com
ScienceDirect
Applied Mathematics and Computation 185 (2007) 883–893
APPLIED MATHEMATICS AND COMPUTATION
www.elsevier.com/locate/amc

Leaf shape based plant species recognition ☆

Ji-Xiang Du [a,b,*], Xiao-Feng Wang [b], Guo-Jun Zhang [a,b]

[a] *Department of Automation, University of Science and Technology of China, Hefei, Anhui 230027, China*
[b] *Intelligent Computing Lab, Institute of Intelligent Machines, Chinese Academy of Sciences, P.O. Box 1130, Hefei, Anhui 230031, China*

Abstract

Plant has plenty use in foodstuff, medicine and industry. And it is also vitally important for environmental protection. However, it is an important and difficult task to recognize plant species on earth. Designing a convenient and automatic recognition system of plants is necessary and useful since it can facilitate fast classifying plants, and understanding and managing them. In this paper, a leaf database from different plants is firstly constructed. Then, a new classification method, referred to as move median centers (MMC) hypersphere classifier, for the leaf database based on digital morphological feature is proposed. The proposed method is more robust than the one based on contour features since those significant curvature points are hard to find. Finally, the efficiency and effectiveness of the proposed method in recognizing different plants is demonstrated by experiments.

Keywords: Digital morphological feature; Plant recognition; Leaf database; Hypersphere classifier

1. Introduction

Plant, a biology existing everywhere, is a greatly significant thing for human's living and development. All over the world, there are currently about 310 000–420 000 known plant species, and many are still unknown yet.

At present, plant taxonomy usually adopts traditional classification method. And so far many other classification methods, such as morphologic anatomy, cell biology, molecule biology, phytochemistry, have also been used. These methods have great relation to do with biology and chemistry. Nevertheless, the acquisition of needed data from plant living body or specimen directly and automatically by computer has not been implemented [1].

With the deterioration of environments, more and more rare plant species are at the margin of extinction. Many of rare plants have died out. Nowadays, there are about 22–47% plant species of all known plants that

☆ This work was supported by the National Science Foundation of China (Nos. 60472111 and 60405002).
* Corresponding author. Address: Intelligent Computing Lab, Institute of Intelligent Machines, Chinese Academy of Sciences, P.O. Box 1130, Hefei, Anhui 230031, China.
E-mail addresses: du_jx@iim.ac.cn (J.-X. Du), xfwang@iim.ac.cn (X.-F. Wang).

0096-3003/$ - see front matter
doi:10.1016/j.amc.2006.07.072

are endangered, of which, there are about 100 000–150 000 plants that probably will die out in short time. So, it's necessary and urgent for us to establish bio-diversity database by information technology as soon as possible [2–7].

Since recent decades, digital image processing, image analysis and machine vision have been sharply developed, and they have become into a very important part of artificial intelligence and the interface between human and machine grounded theory and applied technology. These technologies have been applied widely in industry and medicine, but rarely in realm related to agriculture.

Our research work in this paper is introducing digital image processing theory into the numerical taxonomy in botany. Generally, the digital morphological features are most conventional and widely used. Thus, this efficient feature extraction method is adopted in this paper. By computing the digital morphological features of some kinds of plant species, plants can be classified automatically.

This paper is organized as follows: Section 2 introduces the image acquisition preprocessing method. In Section 3, digital morphological feature extraction method is described and discussed. Section 4 presents the fundamental principle of a new move median centers (MMC) hypersphere classifier. The experimental results are presented in Section 5, and Section 6 concludes the whole paper and gives related conclusions.

2. Image acquisition and preprocessing

In this section, we introduce how to acquire plant leaf and present the preprocessing procedure on the plant leaf. It's very necessary for later work of digital morphological feature extraction of plant leaf.

2.1. Acquisition of plant leaf

Plants can be usually identified according to the shapes, colors, textures and structures of their leaf, bark, flower, seedling and morph. However, it is very difficult for ones to analyze the shapes of flowers, seedling and morph of plants for their complex 3D structures if based on only 2D images. So in our research work, we will identify different plants by leaf features. Leaves are usually firstly clustered so that it is not easy for us to automatically extract features of leaves from the complex background. The leaf image database used in the following experiment is collected and built by ourselves in our lab. The procedure is that we pluck the leaf from plant, put it on the scanner, and then take the digital color image of the leaf directly, or put it on a panel, take digital color image of the leaf with a digital camera. In this way, we can get an image including only one leaf, and the background of the leaf image will be blurred.

This database includes 20 species of different plants. Each species includes 20 sample images. Hence there are totally 400 images with the database. The representative sample images for the 20 species in the database are shown in Figs. 1 and 2.

2.2. Leaf image preprocessing

The colors of plant leaves are usually green (as shown in Fig. 3(a)). Moreover, the shades and the variety of changes of water, nutrient, atmosphere and season can cause change of the color, so the color feature has low reliability. Thus, we decided to recognize various plants by the grey-level image of plant leaf (as shown in

Fig. 1. Different plant species in leaf database.

Fig. 2. Different samples in the same class.

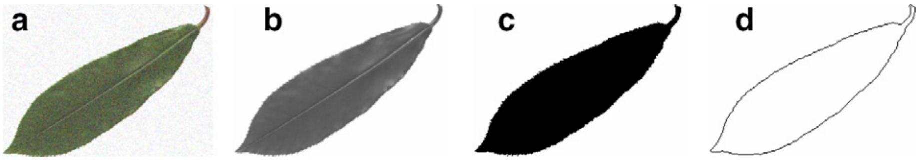

Fig. 3. The processed leaf images: (a) color image, (b) gray image (c) binary image and (d) leaf contour.

Fig. 3(b)), while ignoring the color information. As a result, only Gray component for each pixel is computed from the color image by

$$\mathrm{Gray} = 0.299 * \mathrm{R} + 0.578 * \mathrm{G} + 0.114 * \mathrm{B}, \tag{1}$$

where R, G, B correspond to the color of the pixel [8,9], respectively.

The rectangle of interest (ROI) of leaf image should include all the pixels their gray values are smaller than a specific threshold, then the binary image of leaf as shown in Fig. 3(c) is got. In our study the threshold is automatically got according to the histogram of the leaf gray image. Then the contour of leaf can be extracted from the binary image by the operators of mathematical morphology (as shown in Fig. 3(d)) [8,9].

3. Digital morphology features extraction

In this section, we introduce how to extract digital morphology features. The features are extracted from the contours of leaf. The digital morphology features (DMF) generally include geometrical features (GF) and invariable moment features (MF). The geometrical features consist of aspect ratio, rectangularity, area ratio of convexity, perimeter ratio of convexity, sphericity, circularity, eccentricity and form factor, etc.

3.1. Aspect ratio

The aspect ratio is a ratio between the maximum length $D_{\max}$ and the minimum length $D_{\min}$ of the minimum bounding rectangle (MBR)

$$\mathrm{AR} = \frac{D_{\max}}{D_{\min}}. \tag{2}$$

3.2. Rectangularity

The rectangularity, representing the ratio of ROI area and the MBR area, is calculated by

$$R = \frac{A_{\mathrm{ROI}}}{D_{\max} \times D_{\min}}. \tag{3}$$

3.3. Area ratio of convex hull

The area ratio of convex hull, representing the ratio of the ROI area A_{ROI} and the convex hull area A_{C}, is calculated by

$$\mathrm{CA} = \frac{A_{\mathrm{ROI}}}{A_{\mathrm{C}}}. \tag{4}$$

3.4. Perimeter ratio of convex hull

The perimeter ratio of convex hull, representing the ratio of the ROI perimeter P_{ROI} and the convex hull perimeter P_{C}, is calculated by

$$\mathrm{CP} = \frac{P_{\mathrm{ROI}}}{P_{\mathrm{C}}}. \tag{5}$$

3.5. Sphericity

The sphericity is defined as

$$S = \frac{r_{\mathrm{i}}}{r_{\mathrm{c}}}, \tag{6}$$

where r_{i} represents the radius of incircle of the ROI, and r_{c} the radius of the excircle of the ROI.

3.6. Circularity

The circularity is defined by all of the bounding points of the ROI

$$C = \frac{\mu_{\mathrm{R}}}{\sigma_{\mathrm{R}}}, \tag{7}$$

where μ_{R} is the mean distance between the center of the ROI and all of the bounding points, and σ_{R} is the quadratic mean deviation of the mean distance:

$$\mu_{\mathrm{R}} = \frac{1}{N}\sum_{i=0}^{N-1} \|(x_i, y_i) - (\bar{x}, \bar{y})\|, \tag{8}$$

$$\sigma_{\mathrm{R}} = \frac{1}{N}\sum_{i=0}^{N-1} (\|(x_i, y_i) - (\bar{x}, \bar{y})\| - \mu_{\mathrm{R}})^2. \tag{9}$$

3.7. Eccentricity

The eccentricity is defined as the ratio of the length of main inertia axis of the ROI E_{A} to the length of minor inertia axis of the ROI E_{B}

$$E = \frac{E_{\mathrm{A}}}{E_{\mathrm{B}}}. \tag{10}$$

3.8. Form factor

The form factor is a popular shape description characteristic independent of linear transformations given by

$$F = \frac{4\pi A_{\mathrm{ROI}}}{P_{\mathrm{ROI}}^2}. \tag{11}$$

The convex hull, ellipse, MBR and incircle and excircle of the leaf ROI are shown in Fig. 4.

3.9. Invariant moments

Besides the above features, the moments are also widely used as the features for image processing and classification, which provide a more geometric and intuitive meaning than the morphological features. It was Hu who first set out the mathematical foundation for two-dimensional moment invariants. Hu defined seven

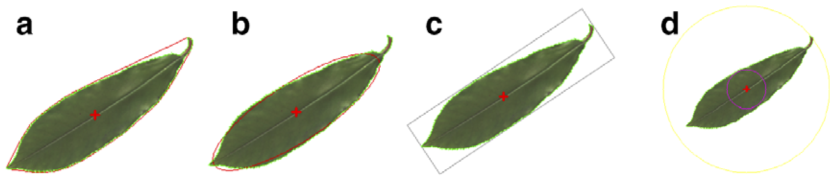

Fig. 4. The leaf ROI (a) convex hull, (b) ellipse, (c) MBR and (d) Incircle and excircle.

invariant moments computed from central moments through order three that are also invariant under object translation, scaling and rotation. Accordingly, we consider using these Hu moment invariants as classification features in this paper. Their values can be calculated from the contours using Chen's improved moments [10] as follows:

The Chen's improved geometrical moments of order $(p+q)$ are defined as

$$M_{pq} = \int_C x^p y^q \mathrm{d}s, \tag{12}$$

where $p, q = 0, 1, 2, \ldots, \int_C$ is the line integral along a closed contour C, and $\mathrm{d}s = \sqrt{(\mathrm{d}x)^2 + (\mathrm{d}y)^2}$.

For the purpose of practical implementation, M_{pq} could be computed in their discrete form

$$M_{pq} = \sum_x \sum_y x^p y^q. \tag{13}$$

Then the contour central moments can be calculated as follows:

$$\mu_{pq} = \int_C (x-\bar{x})^p (y-\bar{y})^q \mathrm{d}s, \tag{14}$$

$$\bar{x} = \frac{M_{10}}{M_{00}}, \quad \bar{y} = \frac{M_{01}}{M_{00}}. \tag{15}$$

For the discrete case, the above μ_{pq} becomes

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q, \tag{16}$$

where $\gamma = \frac{p+q}{2} + 1$, $p+q = 2, 3, 4, \ldots$

These new central moments are further normalized using the following formula:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}. \tag{17}$$

Consequently, a set of seven invariant moments can be derived from the normalized central moments

$$\begin{aligned}
Hu1 &= \eta_{20} + \eta_{02}, \\
Hu2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2, \\
Hu3 &= (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2, \\
Hu4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{03} + \eta_{21})^2, \\
Hu5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{03} + \eta_{21})^2] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2], \\
Hu6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{03} + \eta_{21}), \\
Hu7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{03} + \eta_{21})^2] \\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2].
\end{aligned} \tag{18}$$

4. MMC hypersphere classifier

4.1. Algorithm of MMC

The fundamental idea of the MMC is that each class of patterns are regarded as a series of "hyperspheres", which is treated as a set of "points" in conventional approaches [11,12]. The first step of MMC is to compute the multidimensional median of the points of the considered class, set the initial center as the point that is closest to that median, find the maximum radius that can encompass the points of the class. Through certain iteration we remove the center of the hypersphere in a way that would enlarge the hypersphere and have it encompass as many points as possible. This is performed by having the center "hop" from one data point to a neighboring point. Once we find the largest possible hypersphere, the points inside this hypersphere are removed, and the whole procedure is repeated for the remaining points of the class. We continue until all points of that class are covered by some hyperspheres. At that point, we tackle the points of the next class in a similar manner. The final step is to remove redundant hyperspheres, which are totally encompassed by a larger hypersphere. The detailed steps of the algorithm are stated as follows:

Step 1: Set $K = 1$, $C = 1$, $S =$ all points of class C.
Step 2: Find the median of the points of S.
Step 3: Select the closest point P_y to that median as the initial center of a hypersphere K.
Step 4: Find the nearest point P_z of a different class from the center, and let D_1 be the distance between P_y and P_z.
Step 5: Find the farthest point of the same class inside the hypersphere of radius D_1 to the center. Let D_2 be the distance from the center to that farthest point.
Step 6: Set the radius of hypersphere K as $(D_1 + D_2)/2$.
Step 7: Search among the nearest E points of the same class C that are in the negative direction with respect to the direction of P_z–P_y. The purpose is to move the center to the new point to enlarge the hypersphere. The point, which has the most negative direction, is selected to replace P_y as the new center.
Step 8: If there is no point in the negative direction that we can move to, the hypersphere K has been completed, else repeat steps 5–7.
Step 9: Remove the points encompassed by that hypersphere K from S.
Step 10: Set $K = K + 1$. If S is not empty repeat steps 2–9, else set $C = C + 1$, and operate on the new class by running steps 1–9.

4.2. MMC classification stage

After the training of the MMC is finished, any given data point can be classified by the MMC. We have chosen to use the distance to the outside surface of the hypersphere as the selection criterion. If the point is inside the hypersphere, the distance will be negative. Specifically, to get the class information for any input sample, we perform the following steps:

- Compute the distance D_i between the data point and the center of each hypersphere H_i.
- The index for nearest neighbor Hypersphere I_q is chosen as

$$I_q = \mathop{\arg\min}_{i \in \{1,2,3,\ldots,H\}} \left(\frac{D_i}{R_i} - 1 \right) - \varepsilon, \tag{19}$$

where H is the total number of hyperspheres, R_i is the radius of hypersphere H_i.

4.3. Data preprocessing for application of the MMC to plant recognition

The digital features extracted from plant leaves usually have large range in numerical values, we should normalize all the elements in the feature vector to a new one as follows:

$$\overline{X}_{ij} = \frac{X_{ij} - \theta_{j\mathrm{Min}}}{X_{j\mathrm{Max}} - \theta_{j\mathrm{Min}}}, \tag{20}$$

where X_{ij} is the jth element of feature vector X_i, $\theta_{j\mathrm{Max}}$ is the maximum value of jth element of all vectors from different classes and $\theta_{j\mathrm{Min}}$ is the minimum value of the jth element of all vectors from different classes.

The data usually contain noises, which result in overlapping samples in pattern space [13,14], and there may produce some outliers in the training data set. So we need to remove these outliers from the training data set so that a better decision boundary can be easily formed. We here apply Wilson Editing method to remove those points that do not agree with the majority of their k nearest neighbors [15–17].

5. Experimental results

The experiments were designed to classify each test image into a single class. Since all the leaf images are taken by ourselves, their true classes are known. In our experiment, we recognize the plant by the MMC classifier. We also do the performance comparison of the MMC classifier with the nearest neighbor (1-NN) method and k-NN method [18–20].

Firstly, we select ten of the samples as training samples, and the remaining is used as testing samples. Fig. 5 shows the histogram of hypersphere radiuses of training samples, and the correct rate of classification of every

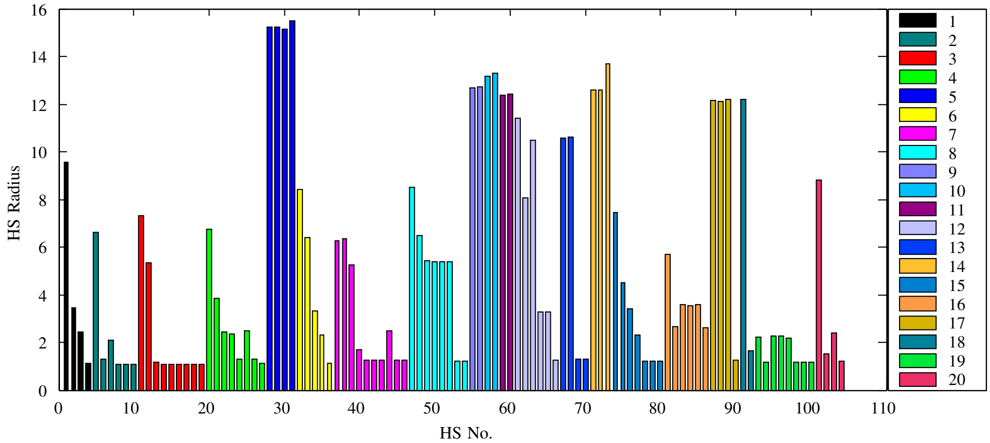

Fig. 5. The histogram of hypersphere radiuses.

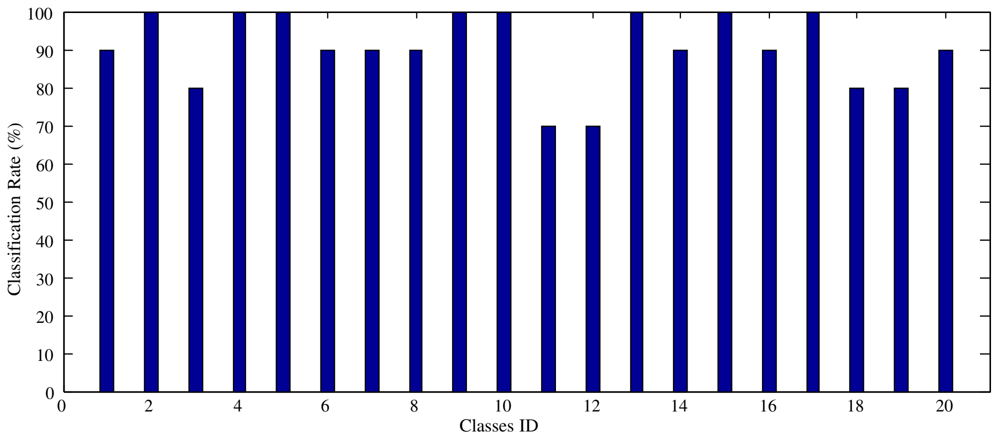

Fig. 6. Classification rate of every class.

Table 1
The performance comparison for three classifiers

	MMC	1-NN	4-NN
Training time (mm)	15	/	/
Classification time (mm)	14	18	96
Storage vector	104	200	200
Correct rate (%)	91	93	92

class is shown in Fig. 6. As a result, the training times consumed of the MMC, the classification times, the storage vector numbers and the mean correct recognition rate for the three classifiers can be obtained, respectively, as shown in Table 1.

To do more performance comparison, we select i ($i = 1, 2, 3 \ldots, 19$) samples as training data, then the rest $(20 - i)$ is as test data. The results are respectively shown in Figs. 6–11.

From Table 1 Figs. 7 and 9, it can be seen that the storage vector number for the former is smaller than the ones for the latter two and the correct recognition rate for the MMC is slightly lower than the others. Fig. 8 shows that the classification time consumed for the MMC is shorter than the ones for 1-NN and the 4-NN classifiers. Though the training time of the MMC is close to the one of the 1-NN classifier, the training of the MMC is only once finished for given training samples. Fig. 10 shows that the digital morphological

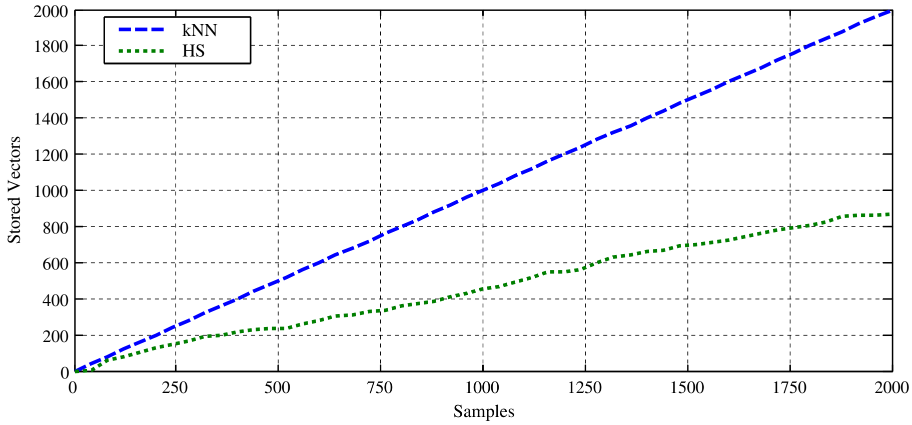

Fig. 7. The storage vector comparison.

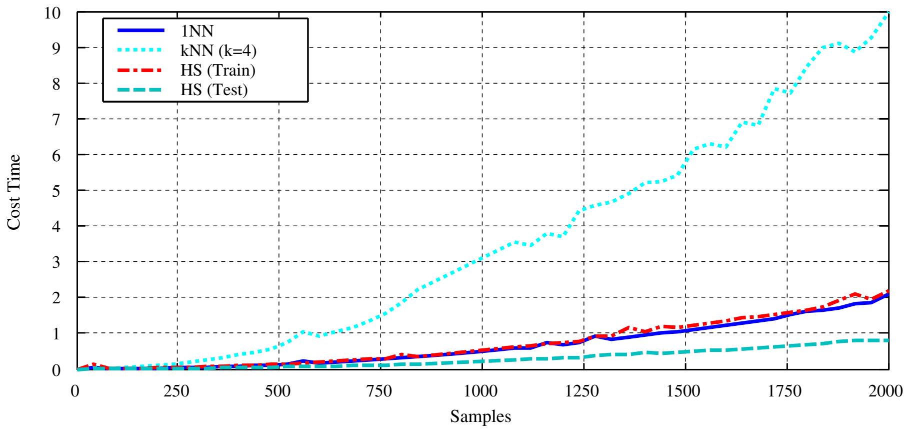

Fig. 8. The consumed time comparison.

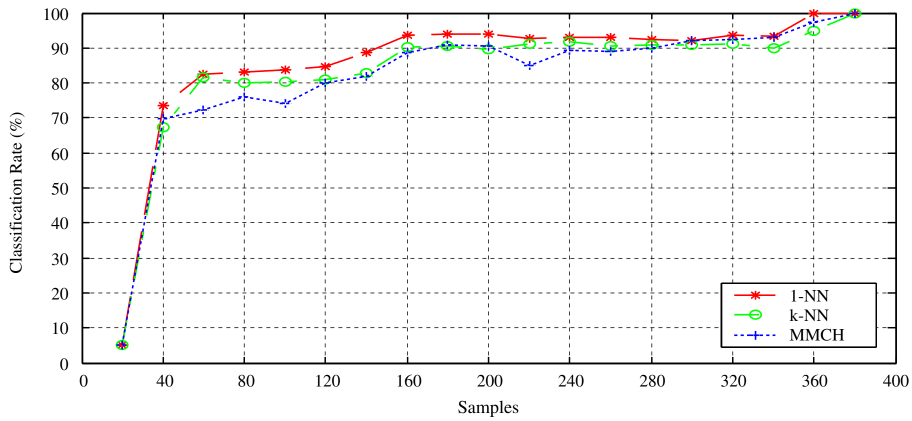

Fig. 9. The classification rate comparison.

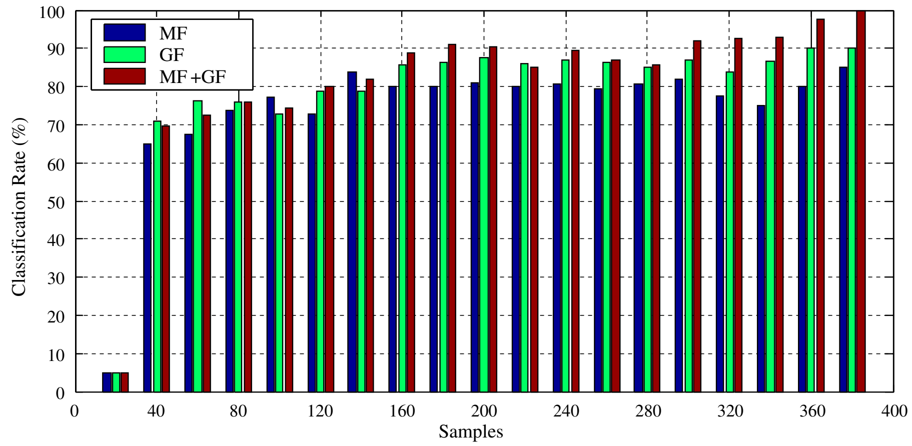

Fig. 10. The comparison of features.

features we extracted is efficient for plant recognition. When the training samples of every class are to exceed three samples, the correct recognition rate is greater than 75%. In addition, it can be seen that the number of moveable points E has effect on the recognition rate (as shown in Fig. 11), but this effect is slighter than the

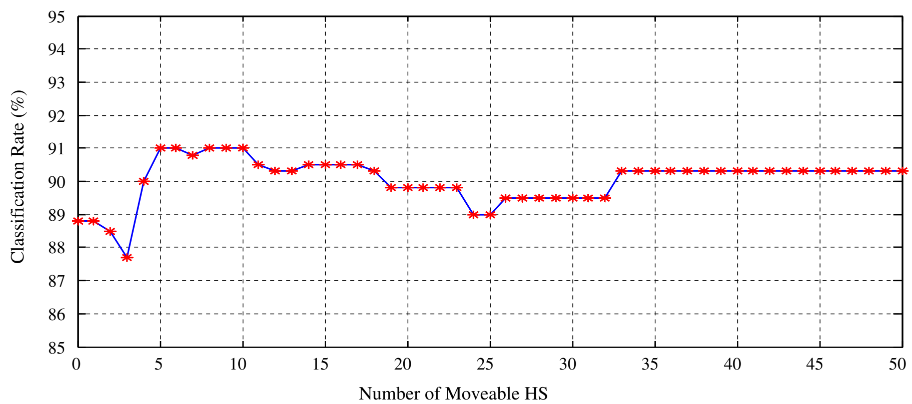

Fig. 11. The affection of E.

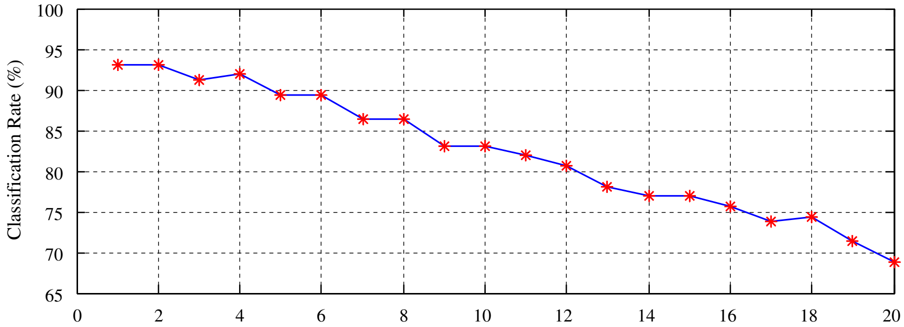

Fig. 12. The affection of k.

effect of the k on the k-NN classifier (as shown in Fig. 12). Therefore, it can be deduced that when existing a large amount of samples, the MMC hypersphere classifier is a more preferred candidate than the 1-NN and the k-NN classifiers.

6. Conclusions

In this paper, a digital morphological feature based automatic recognition method for plant images was proposed and performed. The fifteen features are used to classify 20 species of plant leaves. In addition, a new moving median centers hypersphere classifier is adopted to perform the classification. The experimental results demonstrated that the proposed method is effective and efficient. In particular, by comparing with the 1-NN and k-NN classifiers, it can be found that the MMC classifier can not only save the storage space but also reduce the classification time under the case of no sacrificing the classification accuracy.

References

[1] Ji-Xiang Du, Xiao-Feng Wang, D.S. Huang, Automatic plant leaves recognition system based on image processing techniques, Technical Report, Institute of Intelligent Machines, Chinese Academy of Sciences, October, 2004.

[2] S. Abbasi, F. Mokhtarian, J. Kittler, 'Reliable classification of chrysanthemum leaves through curvature scale space', in: International Conference on Scale-Space Theory in Computer Vision, Netherlands, 1997, pp. 284–295.

[3] Cholhong Im, H. Nishida, Recognizing plant species by normalized leaf shapes, Vision Interf. (1999) 397–404.

[4] T. Saitoh, T. Kaneko, Automatic recognition of wild flowers, Proc. Pattern Recog. 2 (2000) 507–510.

[5] Z. Wang, Z. Chi, D. Feng, Fuzzy integral for leaf image retrieval, Proc. Fuzzy Syst. 1 (2002) 372–z377.

[6] Z. Wang, Z. Chi, D. Feng, Shape based leaf image retrieval, Image Signal Process. 150 (1) (2003) 34–43.

[7] Anxiang Hong, Z. Chi, Region-of-interest based flower image retrieval, ICASSP 3 (2003) 589–592.

[8] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, second ed., Publishing House of Electronics Industry, Beijing, 2004.

[9] Milan Sonka, Vaclav Hlavac, Roger Boyle, Image Processing, Analysis, and Machine Vision, second ed., People's Post & Telecommunications Publishing House, Beijing, 2003.

[10] Chaur-Chin Chen, Improved moment invariants for shape discrimination, Pattern Recog. 26 (5) (1993) 683–686.

[11] Guo-Jun Zhang, Xiao-Feng Wang, D.S. Huang, Zheru Chi, Yiu-Ming Cheung, Ji-Xiang Du and Yuan-Yuan Wan, 'A hypersphere method for plant leaves classification', in: Proceedings of the 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing (ISIMP 2004), October 20–22, 2004, Hong Kong, China, pp. 165–168.

[12] Yuan-Yuan Wan, Ji-Xiang Du, D.S. Huang, Zheru Chi, Yiu-Ming Cheung, Xiao-Feng Wang, Guo-Jun Zhang, 'Bark texture feature extraction based on statistical texture analysis', in: Proceedings of The 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing (ISIMP 2004), October 20–22, 2004, Hong Kong, China, pp. 482–485.

[13] D.S. Huang, Systematic Theory of Neural Networks for Pattern Recognition, Publishing House of Electronic Industry of China, Beijing, 1996.

[14] D.S. Huang, The local minima free condition of feed forward neural networks for outer-supervised learning, IEEE Trans. Syst. Man Cybernet. 28B (3) (1998) 477–480.

[15] B.V. Dasarathy, Nearest Neighbor NN Norms: NN Pattern Classification Techniques, McGraw-Hill Computer Science Series, IEEE CS Press, 1991.

[16] T.M. Cover, P.E. Hart, Nearest Neighbor Pattern Classification, IEEE. Trans. Inform. Theory 13 (Jan.) (1967) 21–27.

[17] P.E. Hart, The condensed nearest neighbor rule, IEEE Trans. Inform. Theory 14 (3) (1967) 515–516.

[18] R. Paredes, E. Vidal, A nearest neighbor weighted measure in classification problems, in: A. Sanfeliu, M.I. Torres (Eds.), Proc. of the 7th SNRFAI, IOS press, 2000, pp. 44–50.
[19] Douglas Heisterkamp, Jing Peng, HK Dai, "Adaptive quasiconformal kernel metric for image retrieval", in: Proceedings Of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 236–243, 2001.
[20] B.L. Li, S.W. Yu, Qin Lu, An improved k-nearest neighbor algorithm for text categorization, in: M.S. Sun, T.S. Yao, C.F. Yuan (Eds.), Proc. of the 20th Int'l Conf. Comput. Process Oriental Languages, Tsinghua University Press, Beijing, 2003.